

1. Gaussian quadrature rules

Answer in Wikipedia for reference:

Number of points, n	Points, x_i	Weights, w_i
1	0	2
2	$\pm \frac{1}{\sqrt{3}}$	$\pm 0.57735...$
3	0	$\frac{8}{9}$ 0.88889...
	$\pm \sqrt{\frac{3}{5}}$	$\pm 0.774597...$ $\frac{5}{9}$ 0.55556...

By hand, derive the 3-point Gauss-Legendre quadrature rule by guessing the symmetry and requiring that it has polynomial degree 5.

We expect the symmetry $(x_0, x_1, x_2) = (-r, 0, r)$ for some $r \in (0, 1]$, and $w_2 = w_0$. Thus $Q(f) = w_0 f(-r) + w_1 f(0) + w_0 f(r)$.

(If this guess is wrong, we will know about it as the calculation proceeds.)
Want poly degree 5, that is $Q(f) = \int_{-1}^1 f \quad \forall f \in \{1, \cdot, \cdot^2, \cdot^3, \cdot^4, \cdot^5\}$.

(0) $f(x) = 1$
 $w_0 + w_1 + w_0 = \int_{-1}^1 1 dx = 2 \quad : \quad 2w_0 + w_1 = 2 \quad \textcircled{1}$

(1) $f(x) = x$
 $w_0(-r) + w_1(0) + w_0(r) = \int_{-1}^1 x dx = 0 \quad : \quad 0 = 0. \quad \text{Accomplished by the symmetry.}$

(2) $f(x) = x^2$
 $w_0(r)^2 + w_1(0)^2 + w_0 r^2 = \int_{-1}^1 x^2 dx = \frac{2}{3} \quad : \quad 2w_0 r^2 = \frac{2}{3}, \quad w_0 r^2 = \frac{1}{3} \quad \textcircled{2}$

(3) $f(x) = x^3$
 $w_0(-r)^3 + w_1(0)^3 + w_0 r^3 = \int_{-1}^1 x^3 dx = 0 \quad : \quad 0 = 0. \quad \text{Accomplished by the symmetry.}$

(4) $f(x) = x^4$
 $w_0(-r)^4 + w_1(0)^4 + w_0 r^4 = \int_{-1}^1 x^4 dx = \frac{2}{5} \quad : \quad 2w_0 r^4 = \frac{2}{5}, \quad w_0 r^4 = \frac{1}{5} \quad \textcircled{3}$

(5) $f(x) = x^5$. Again by symmetry.

So we have 3 (nonlinear) equations in the 3 unknowns w_0, w_1, r :
 Dividing $\textcircled{3}$ by $\textcircled{2}$, we have $r^2 = \frac{\frac{1}{5}}{\frac{1}{3}} = \frac{3}{5}$, so $r = \sqrt{\frac{3}{5}}$.

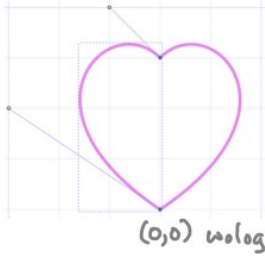
Then $\textcircled{2}$ gives $w_0 \cdot \frac{3}{5} = \frac{1}{3}$, so $w_0 = \frac{5}{9} = w_2$.

Finally $\textcircled{1}$ gives $w_1 = 2 - 2\left(\frac{5}{9}\right) = \frac{18-10}{9}$, $w_1 = \frac{8}{9}$.

Summarizing, $Q(f) = \frac{5}{9} f\left(-\sqrt{\frac{3}{5}}\right) + \frac{8}{9} f(0) + \frac{5}{9} f\left(\sqrt{\frac{3}{5}}\right)$.

2. Using a quadrature rule

Obtain an accurate approximation to the length of this curve made of two Bezier segments, if the grid squares have side 1 meter.



The left half of the curve is a Bézier segment $P(t)$ with $P_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, $P_1 = \begin{bmatrix} -3 \\ 2 \end{bmatrix}$, $P_2 = \begin{bmatrix} -1 \\ 4 \end{bmatrix}$, $P_3 = \begin{bmatrix} 0 \\ 3 \end{bmatrix}$.

The length of the segment is the integral of the speed

$$L = \int_0^1 \text{speed}(t) dt = \int_0^1 \|P'(t)\|_2 dt$$

So we just need to differentiate the formula $P(t)$ and integrate its 2-norm.

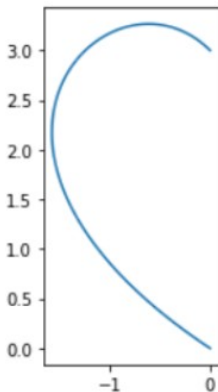
```

1 from nsm import *
2
3 def bezier(P,t): # columns of P are P0, P1, P2, P3
4     P0,P1,P2,P3 = P.T
5     s = 1 - t
6     x = s**3*P0[0] + 3*s**2*t*P1[0] + 3*s*t**2*P2[0] + t**3*P3[0]
7     y = s**3*P0[1] + 3*s**2*t*P1[1] + 3*s*t**2*P2[1] + t**3*P3[1]
8     return x,y
9
10 P = np.array([[0, -3, -1, 0],
11              [0, 2, 4, 3]]) # columns of P are P0, P1, P2, P3
    
```

check curve looks correct

```

1 t = np.linspace(0,1,100)
2 plt.subplot(111,aspect=1)
3 plt.plot(*bezier(P,t));
    
```



compute the speed:

```

1 t = sp.symbols('t')
2 curvex,curvey = bezier(P,t)
3 print('the curve:')
4 display(curvex.expand())
5 display(curvey.expand())
6 print('the velocity:')
7 vx = curvex.expand().diff(t)
8 vy = curvey.expand().diff(t)
9 display(vx)
10 display(vy)
11 print('the speed:')
12 speed = sp.sqrt((vx**2 + vy**2).expand())
13 display(speed)
    
```

the curve:

$$-6t^3 + 15t^2 - 9t$$

$$-3t^3 + 6t$$

the velocity:

$$-18t^2 + 30t - 9$$

$$6 - 9t^2$$

the speed:

$$\sqrt{405t^4 - 1080t^3 + 1116t^2 - 540t + 117}$$

```

1 speedfunc = sp.lambdify(t,speed,'numpy')
2 # check speedfunc
3 print(speedfunc(np.array([0,1])))
    
```

[10.81665383 4.24264069]

Accurately approximate length by numerical quadrature

Before running this, as a sanity check, I'm eyeballing the curve and estimating the length to be about 5.

```
import numpy as np
import sympy as sp
import pylab as plt
%config InlineBackend.figure_format = 'retina'

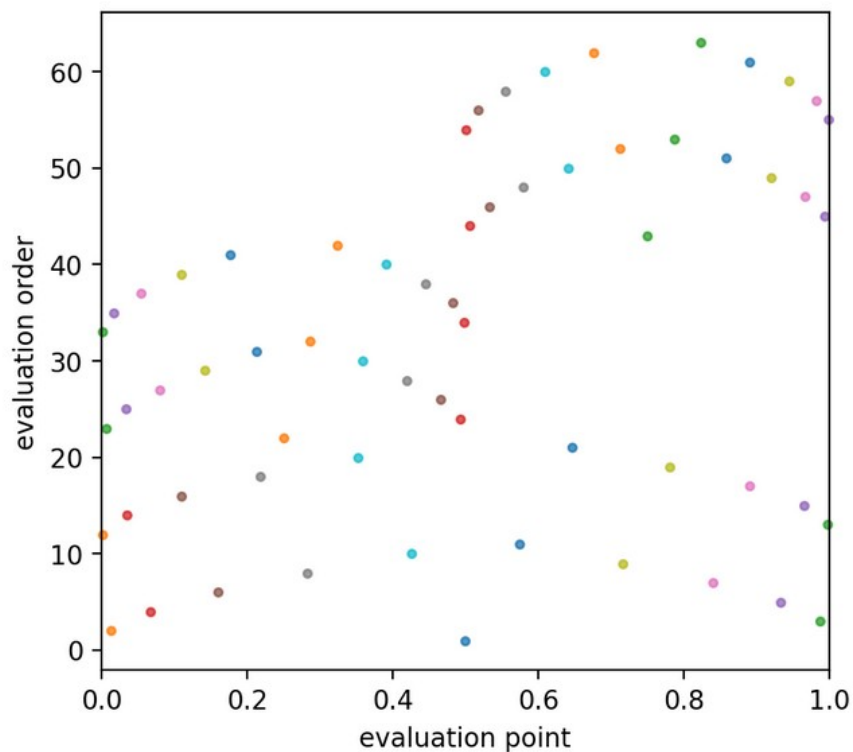
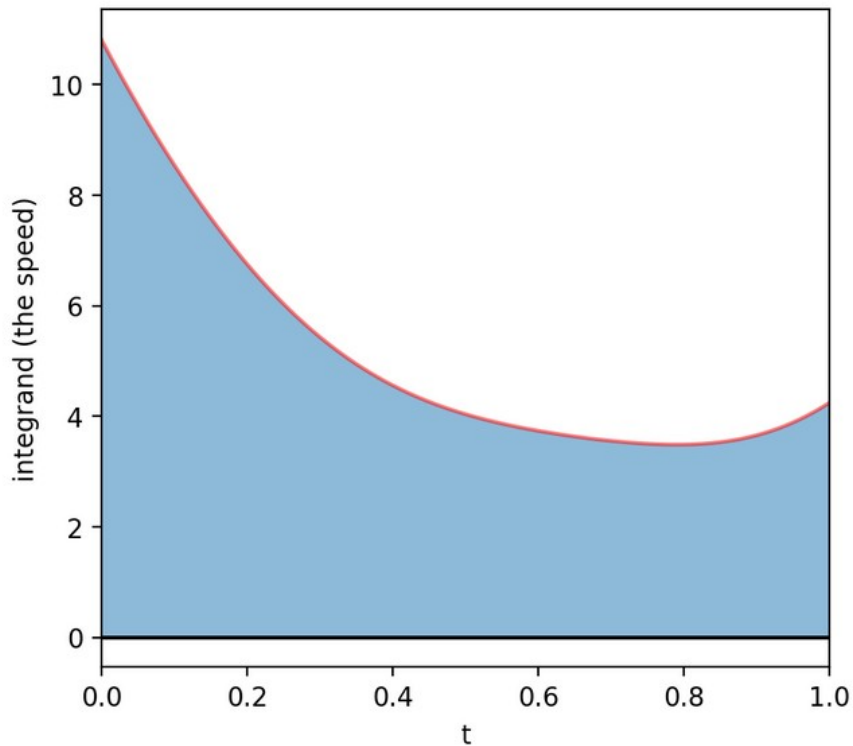
# plot the velocity
def vfunc(t):
    global nevals,ncalls,DIAGNOSTICS
    if DIAGNOSTICS:
        ncalls += 1
        try:
            nevals += len(t)
            print(len(t), 'values requested')
            plt.plot(t,[ncalls]*len(t),'o',ms=3,alpha=.75,clip_on=False)
        except: # t a scalar
            nevals += 1
            plt.plot( t, ncalls, 'o',ms=3,alpha=0.75,clip_on=False)

    return np.sqrt( (-18*t**2 + 30*t - 9)**2 + (6 - 9*t**2)**2 ) # the speed

t = np.linspace(0,1,500)
DIAGNOSTICS = False
v = vfunc(t)
plt.figure(figsize=(5,10))
plt.subplot(211)
plt.fill_between(t,v,alpha=.5);
plt.plot(t,v,alpha=.5,color='r');
plt.axhline(0,color='k')
plt.ylabel('integrand (the speed)'); plt.xlabel('t')
plt.xlim(0,1)

plt.subplot(212)
from scipy.integrate import quad
nevals = 0
ncalls = 0
DIAGNOSTICS = True
I,err = quad( vfunc,0,1)
plt.xlabel('evaluation point')
plt.ylabel('evaluation order')
plt.xlim(0,1)
print('integral estimate:',I)
print('error estimate:',err)
print('number of function evaluations:',nevals)
```

```
integral estimate: 5.103195629014709
error estimate: 7.103803580220992e-13
number of function evaluations: 63
```



The routine quad is evidently using adaptive quadrature with an (11-point, 21-point) rule pair. Googling suggests this is a Gauss-Kronrod pair. A single subdivision was found sufficient to satisfy the default error tolerance.

For the full "heart" curve, we obtain

```
np.round(2*I, 11)
```

10.20639125803

rounding to 13 digits because these, and only these, are expected to be accurate, based on the error estimate.

$$3 \text{ (a) } F\left(\begin{bmatrix} u \\ v \end{bmatrix}\right) = \begin{bmatrix} u^3 - v \\ u^2 + v^2 - 1 \end{bmatrix} \quad F\left(\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right) = \begin{bmatrix} 1^3 - 2 \\ 1^2 + 2^2 - 1 \end{bmatrix} = \begin{bmatrix} -1 \\ 4 \end{bmatrix}$$

$$F'\left(\begin{bmatrix} u \\ v \end{bmatrix}\right) = \begin{bmatrix} 3u^2 & -1 \\ 2u & 2v \end{bmatrix} \quad F'\left(\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right) = \begin{bmatrix} 3 \cdot 1^2 & -1 \\ 2 \cdot 1 & 2 \cdot 2 \end{bmatrix} = \begin{bmatrix} 3 & -1 \\ 2 & 4 \end{bmatrix}$$

1st Newton step $S^{(0)}$ determined by $F'(x^{(0)}) S^{(0)} = -F(x^{(0)})$.

Writing $S^{(0)} = \begin{bmatrix} \delta u \\ \delta v \end{bmatrix}$, that is $\begin{bmatrix} 3 & -1 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} \delta u \\ \delta v \end{bmatrix} = \begin{bmatrix} +1 \\ -4 \end{bmatrix}$

$$\left[\begin{array}{cc|c} 3 & -1 & 1 \\ 2 & 4 & -4 \end{array} \right] \xrightarrow{\textcircled{2} + 4\textcircled{1}} \left[\begin{array}{cc|c} 3 & -1 & 1 \\ 14 & 0 & 0 \end{array} \right] \rightarrow 14\delta u = 0, \boxed{\delta u = 0} \left. \vphantom{\begin{array}{cc|c} 3 & -1 & 1 \\ 14 & 0 & 0 \end{array}} \right\} S^{(0)} = \begin{bmatrix} 0 \\ -1 \end{bmatrix}$$

Then $\textcircled{2} \rightarrow 0 - 1\delta v = 1 \rightarrow \boxed{\delta v = -1}$

Thus $x^{(1)} = x^{(0)} + S^{(0)} = \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \begin{bmatrix} 0 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} = x^{(1)}$

(b) Broyden update of 'jacobian'.

Formula is $B^{(k+1)} = B^{(k)} + \frac{(\Delta^{(k)} - B^{(k)} S^{(k)}) S^{(k)T}}{S^{(k)T} S^{(k)}}$

where $B^{(k)}$ is approx to jacobian at $x^{(k)}$, $\Delta^{(k)}$ is $F(x^{(k+1)}) - F(x^{(k)})$.

Here $B^{(0)} = F'\left(\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right) = \begin{bmatrix} 3 & -1 \\ 2 & 4 \end{bmatrix}$

$$\Delta^{(0)} = F(x^{(1)}) - F(x^{(0)}) = F\left(\begin{bmatrix} 1 \\ 1 \end{bmatrix}\right) - F\left(\begin{bmatrix} 1 \\ 2 \end{bmatrix}\right) = \begin{bmatrix} 1^3 - 1 \\ 1^2 + 1^2 - 1 \end{bmatrix} - \begin{bmatrix} -1 \\ 4 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} - \begin{bmatrix} -1 \\ 4 \end{bmatrix} = \begin{bmatrix} 1 \\ -3 \end{bmatrix}$$

$$S^{(0)} = \begin{bmatrix} 0 \\ -1 \end{bmatrix}, \quad S^{(0)T} = [0, -1], \quad S^{(0)T} S^{(0)} = [0, -1] \begin{bmatrix} 0 \\ -1 \end{bmatrix} = 1.$$

$$\begin{aligned} \text{So } B^{(1)} &= \begin{bmatrix} 3 & -1 \\ 2 & 4 \end{bmatrix} + \left(\begin{bmatrix} 1 \\ -3 \end{bmatrix} - \begin{bmatrix} 3 & -1 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} 0 \\ -1 \end{bmatrix} \right) [0, -1] \\ &= \begin{bmatrix} 3 & -1 \\ 2 & 4 \end{bmatrix} + \left(\begin{bmatrix} 1 \\ -3 \end{bmatrix} - \begin{bmatrix} 1 \\ -4 \end{bmatrix} \right) [0, -1] = \begin{bmatrix} 3 & -1 \\ 2 & 4 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} [0, -1] = \begin{bmatrix} 3 & -1 \\ 2 & 4 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & -1 \end{bmatrix} \\ &= \begin{bmatrix} 3 & -1 \\ 2 & 3 \end{bmatrix}. \end{aligned}$$

The actual 'jacobian' at $x^{(1)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ is $F'\left(\begin{bmatrix} 1 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 3 \cdot 1^2 & -1 \\ 2 \cdot 1 & 2 \cdot 1 \end{bmatrix} = \begin{bmatrix} 3 & -1 \\ 2 & 2 \end{bmatrix}$.

The approximation $B^{(1)}$ is not great. We can attribute this to the large size of the step $S^{(0)}$ so that the secant approximation to the derivative is poor. However, it makes sense that only the 2nd column was altered because it represents δv and only v changed in step 1.

I'll check my arithmetic with Python:

```
1 from nsm import *
2
3 def arr(*x): return np.array(x) # to make it easier to create arrays
4
5 def F(x):
6     u,v = x
7     return arr( u**3 - v, u**2 + v**2 - 1 )
8
9 def Fp(x):
10    u,v = x
11    return arr( arr(3*u**2,-1), arr(2*u,2*v) )
12
13 x0 = arr(1,2)
14 F0 = F(x0)
15 Fp0 = Fp(x0)
16 print('x0',x0)
17 print('F0',F0)
18 print('Fp0',Fp0)
```

```
x0 [1 2]
F0 [-1  4]
Fp0 [[ 3 -1]
      [ 2  4]]
```

```
1 s0 = np.linalg.solve(Fp0,-F0)
2 s0
3 print('s0',s0)
4 x1 = x0 + s0
5 print('x1',x1)
6 F1 = F(x1)
7 Fp1 = Fp(x1)
8 print('F1',F1)
9 print('Fp1',Fp1)
```

```
s0 [ 0. -1.]
x1 [1.  1.]
F1 [0.  1.]
Fp1 [[ 3. -1.]
      [ 2.  2.]]
```

```
1 # Broyden update of Fp0
2 B0 = Fp0
3 Delta0 = F1-F0
4 print('Delta0',Delta0)
5 B1 = Fp0 + np.outer(Delta0 - B0@s0,s0)/np.dot(s0,s0)
6 print('B1',B1)
```

```
Delta0 [ 1. -3.]
B1 [[ 3. -1.]
     [ 2.  3.]]
```

Let's try to solve the system using only Broyden updating

```
1 x = x0
2 B = Fp(x)
3 tol = 1.e-8
4 nsteps = 0
5 while True:
6     s = np.linalg.solve(B,-F(x))
7     newx = x + s
8     newF = F(newx)
9     Delta = newF - F(x)
10    B += np.outer(Delta - B@s , s )/np.dot(s,s)
11    x = newx
12    nsteps += 1
13    if np.linalg.norm(s) < tol:
14        break
15 print('Approximate solution',x,'in',nsteps,'steps')
```

Approximate solution [0.82603136 0.56362416] in 9 steps

Everything agrees with hand-calculation.

4. Sherman-Morrison update

(a) Validate formula

$$(A + uv^T)^{-1} = A^{-1} - \frac{A^{-1}uv^T A^{-1}}{1 + (v^T A^{-1}u)} \quad (\text{assuming denominator } \neq 0, \text{ which will be true for all sufficiently small } u, v).$$

First let's note that for convenience we tend to be a bit sloppy about the distinction between 1-by-1 matrices and scalars. For example, in the denominator $1 + v^T A^{-1}u$, 1 is a scalar, while strictly $v^T A^{-1}u$ is a 1-by-1 matrix. For this question let's use $(v^T A^{-1}u)$ in parentheses to mean the (one) scalar entry of the 1-by-1 matrix $v^T A^{-1}u$.

call it (*)

For the calculation below, let's also note that $Mv^T A^{-1}uN = (v^T A^{-1}u)MN$ for matrices M, N with shapes for which the products are valid.

Compute product of alleged inverse (RHS) with $A + uv^T$

$$\text{RHS} \cdot (A + uv^T) = \left(A^{-1} - \frac{A^{-1}uv^T A^{-1}}{1 + v^T A^{-1}u} \right) (A + uv^T)$$

$$= AA^{-1} - \frac{A^{-1}uv^T A^{-1}A}{1 + (v^T A^{-1}u)} + A^{-1}uv^T - \frac{A^{-1}uv^T A^{-1}uv^T}{1 + (v^T A^{-1}u)}$$

$$= I + \frac{-A^{-1}uv^T + A^{-1}uv^T + (v^T A^{-1}u)A^{-1}uv^T - A^{-1}uv^T A^{-1}uv^T}{1 + (v^T A^{-1}u)}$$

$$= I + \frac{\underbrace{(v^T A^{-1}u)}_{\text{scalar}} A^{-1}uv^T - A^{-1}uv^T \underbrace{A^{-1}uv^T}_{\text{1-by-1 matrix}}}{1 + (v^T A^{-1}u)}$$



$$= I + \frac{(v^T A^{-1}u) A^{-1}uv^T - (v^T A^{-1}u) A^{-1}uv^T}{1 + (v^T A^{-1}u)} \quad \text{by identity (*)}$$

$$= I + \frac{0}{1 + v^T A^{-1}u} = I \quad \text{QED } \text{☺}$$

Pictorially,

$$\begin{bmatrix} \color{red}{\square} & \color{green}{\square} \end{bmatrix} \mathbf{A} = \begin{bmatrix} \color{gray}{\square} \end{bmatrix} \mathbf{I}$$

$$\color{orange}{\square} = \color{blue}{\square} \color{red}{\square} \color{magenta}{\square}$$

$$\left[\begin{bmatrix} \color{red}{\square} & - \color{red}{\square} \color{magenta}{\square} \color{blue}{\square} \color{red}{\square} \end{bmatrix} \right] \left[\begin{bmatrix} \color{green}{\square} & + \color{magenta}{\square} \color{blue}{\square} \end{bmatrix} \right]$$

$1 + \color{orange}{\square}$

$$= \color{red}{\square} \color{green}{\square} - \frac{\color{red}{\square} \color{magenta}{\square} \color{blue}{\square} \color{red}{\square} \color{green}{\square}}{1 + \color{orange}{\square}} + \color{red}{\square} \color{magenta}{\square} \color{blue}{\square} - \frac{\color{red}{\square} \color{magenta}{\square} \color{blue}{\square} \color{red}{\square} \color{magenta}{\square} \color{blue}{\square}}{1 + \color{orange}{\square}}$$

$$= \color{gray}{\square} - \frac{\color{red}{\square} \color{magenta}{\square} \color{blue}{\square} \color{gray}{\square}}{1 + \color{orange}{\square}} + \color{red}{\square} \color{magenta}{\square} \color{blue}{\square} - \frac{\color{red}{\square} \color{magenta}{\square} \color{blue}{\square} \color{red}{\square} \color{magenta}{\square} \color{blue}{\square}}{1 + \color{orange}{\square}}$$

$$= \color{gray}{\square} - \frac{\color{red}{\square} \color{magenta}{\square} \color{blue}{\square} \color{gray}{\square}}{1 + \color{orange}{\square}} + \color{red}{\square} \color{magenta}{\square} \color{blue}{\square} - \frac{\color{red}{\square} \color{magenta}{\square} \color{orange}{\square} \color{blue}{\square}}{1 + \color{orange}{\square}}$$

$$= \color{gray}{\square} - \frac{\color{red}{\square} \color{magenta}{\square} \color{blue}{\square} \color{gray}{\square}}{1 + \color{orange}{\square}} + \color{red}{\square} \color{magenta}{\square} \color{blue}{\square} - \frac{\color{orange}{\square} \color{red}{\square} \color{magenta}{\square} \color{blue}{\square}}{1 + \color{orange}{\square}}$$

$$= \color{gray}{\square} - \frac{\color{red}{\square} \color{magenta}{\square} \color{blue}{\square}}{1 + \color{orange}{\square}} + \color{red}{\square} \color{magenta}{\square} \color{blue}{\square} - \frac{\color{orange}{\square} \color{red}{\square} \color{magenta}{\square} \color{blue}{\square}}{1 + \color{orange}{\square}}$$

$$= \color{gray}{\square} + \frac{- \color{red}{\square} \color{magenta}{\square} \color{blue}{\square} + (1 + \color{orange}{\square}) \color{red}{\square} \color{magenta}{\square} \color{blue}{\square} - \color{orange}{\square} \color{red}{\square} \color{magenta}{\square} \color{blue}{\square}}{1 + \color{orange}{\square}}$$

$$= \color{gray}{\square}$$

where a 1x1 matrix on the left means scalar multiplication by its one element.

(b) The update $\frac{A^{-1}uv^T A^{-1}}{1 + v^T A^{-1}u}$ has the form $\frac{\boxed{A^{-1}} \boxed{u} \boxed{v^T} \boxed{A^{-1}}}{\text{scalar}}$

If we compute it as $\underbrace{\left(\boxed{A^{-1}} \boxed{u} \right)}_{\text{scalar}} \boxed{v^T} \boxed{A^{-1}} = \boxed{\phantom{A^{-1}}} \boxed{} \boxed{} \boxed{\phantom{A^{-1}}} = \boxed{\phantom{A^{-1} u v^T A^{-1}}}$

$O(n^2)$ $O(n^2)$ $O(n^2)$

we are not doing anything that costs $O(n^3)$ ops.

(If we did it like this, though, $\boxed{\phantom{A^{-1}}} \left(\boxed{} \boxed{} \right) \boxed{\phantom{A^{-1}}} = \boxed{\phantom{A^{-1}}} \boxed{} \boxed{} \boxed{\phantom{A^{-1}}} = \boxed{\phantom{A^{-1} u v^T A^{-1}}}$
it would cost $O(n^3)$.)

$O(n^3)$